ECP POSTER+NETWORKING INDONESIA 2024

APN ASIA-PACIFIC NETWORK FOR GLOBAL CHANGE RESEARCH

Mapping Mangrove Above-Ground Carbon Using Multi-Source Remote Sensing Data and Machine Learning Approach in Loh Buaya, Komodo National Park, Indonesia

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Introduction

Mangroves play a crucial role in providing ecological and provisioning services, such as sequestering atmospheric CO2 (Kumari & Rathore, 2021) and providing habitat for shorebirds and fish (Buelow & Sheaves, 2015). However, they have been lost worldwide due to human disturbance, particularly in Southeast Asia (Fauzi et al., 2019). Sustainable mangrove forest replantation and management are essential. Mangroves have biophysical parameters related to ecosystem health and dynamics (Sani et al., 2018). Accurate measurements of these parameters can be achieved using field investigations, but this method is laborious and time-consuming due to the complexity of the mangrove environment and dangerous fauna (Saintilan et al., 2022).

Remote sensing offers a complementary tool for mangrove carbon measurements, offering a synoptical overview, spectral and spatial resolution, and ease of data capture (Tran et al., 2022). The use of remotely sensed optical and Synthetic Aperture Radar (SAR) images has been successfully applied to develop mangrove carbon models. However, there is a need for improved accuracy in mangrove carbon models (Wang et al., 2019).

This study aims to test a novel Machine Learning (ML) (Figure 1) method proposed by (Pham et al., 2020) to map and quantify mangrove above-ground carbon (AGC) in Indonesian mangroves using multisource free-of-charge remotely sensed datasets. The model integrates extreme gradient boosting (XGB) and genetic algorithm (GA) to map AGB mangroves in Northern Vietnam using optical and SAR data combined with field sampling.

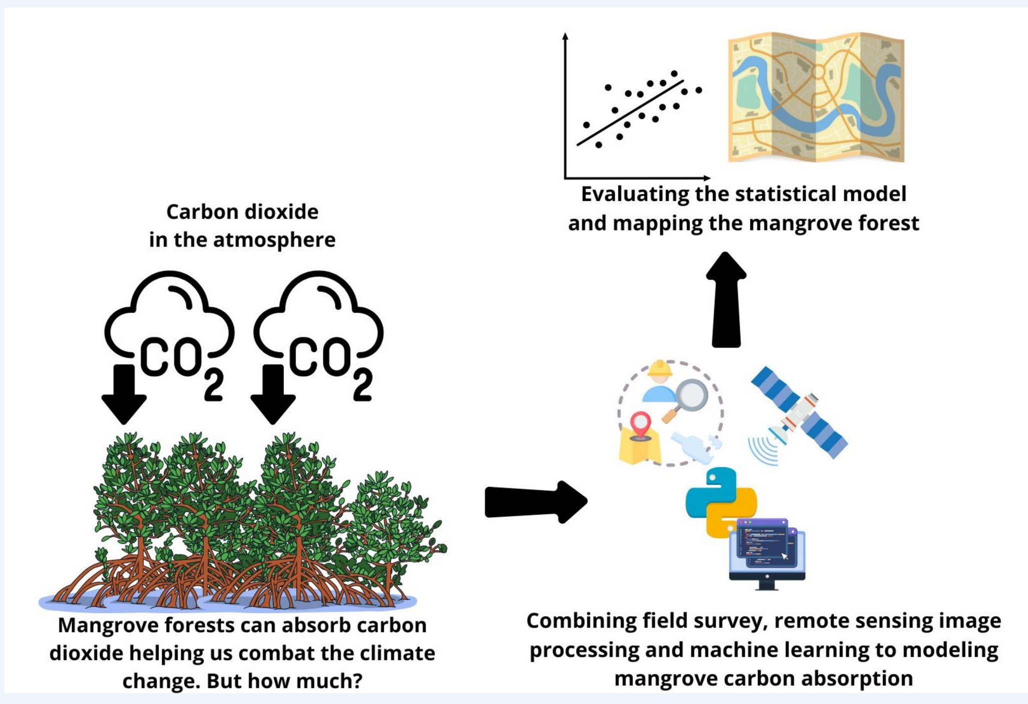

Figure 1. Study aims to test a novel Machine Learning (ML) method for mangrove Above-Ground Carbon (AGC) mapping

Methodology

Field Data Collection

Data were collected from 50 plots sampling across four dominant species of mangroves found in the study area: *Ceriops decandra, Lumnitzera racemosa, Rhizophora apiculata, and Rhizophora mucronata*. Plots consisted of 10 m x 10 m squares established during the field campaign of July 2022 (dry season) using a technique by (I. W. E. Dharmawan et al., 2020) (Figure 2). Measurement in every plot comprised coordinate tagging using a handheld Global Positioning System (GPS: Garmin 64s series with ± 3 m x-y accuracy), Girth at Breast Height (GBH), percentage of canopy cover using hemispherical photography, mangroves species, and substrate identification. MonMang, a smartphone logbook application for mangrove surveys developed by Lembaga Ilmu Pengetahuan Indonesia (LIPI) (I. W. Dharmawan & Sastrosuwondo, 2014) was used to record field data.

Figure 2. Mangrove field measurement

Satellite Image Processing and Machine Learning Approach

We adopted an innovative ML framework introduced by (Pham et al., 2020) to estimate mangrove AGC. However, in this study, a combination of multiple EO source data with free-of-charge Sentinel-2B and Sentinel-1A imagery and a national DEM as elevation data was used to improve the prediction accuracy. Several steps were conducted to derive and test models as follows: (1) Pre-processing and processing of the multiple EO sources, (2) Creating training and testing datasets by combining field sampling data and EO data extraction, (3) Evaluating Machine Learning models, (4) Selecting the optimal variables using the Genetic Algorithm and the highest ML model, (5) Model re-evaluation for mangrove AGC estimations in the study area. The flowchart of this study is shown in Figure 3.

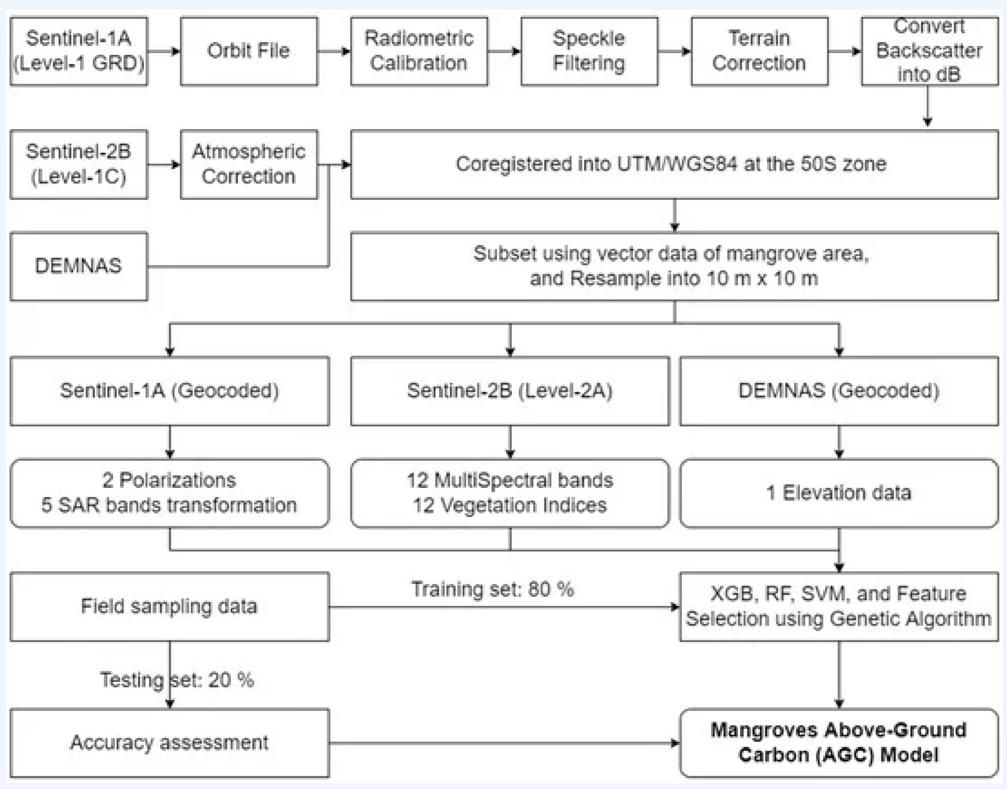

Figure 3. Flowchart for mangrove AGC retrieval developed in the study.

Results

Mangrove Forest Characteristics

Mangroves in the study area also had varying DBH, ranging from 7.48 cm in plot 5 (*Rhizophora apiculata*) to 19.21 cm in plot 27 (*Rhizophora mucronata*) with an average of 12.67 cm. Based on the calculated results of AGC listed in Table 3, the lowest carbon stock was 13.63 Mg C ha⁻¹ in Plot 14 while the largest carbon stock was found in Plot 27 with 143.94 Mg C ha⁻¹. An average AGC was observed at approximately 57.51 Mg C ha⁻¹. The dominant species in the sampling plots were *Rhizophora apiculata*, which was common in 23 of the 50 plots. The calculation of carbon stock is influenced by DBH and wood density, therefore, although *Rhizophora apiculata* had the lowest DBH, this is not corresponding with the lowest carbon stock due to its wood density being higher than *Ceriops decandra*.

Model Comparison and Important Variables

Table 1 compare the model performance of the three ML techniques with all input variables derived from S2B MSI, VIs, and S1A together with SAR transformation as well as DEM and the proposed hybrid XGB-GA model with the optimal 12 features. The hybrid model XGB-GA yielded the highest performance in both the training phase (R^2 = 0.857) and the testing phase (R^2 = 0.758) and had an RMSE = 15.40 Mg C ha⁻¹ for mangrove AGC estimation in the study site. The XGB-GA model incorporating the S2B (6 MS bands), and VIs (5 bands) together with DEM data achieved the highest performance, reflecting a good fit between the model estimates and field-based measurements. The next-highest performers in the testing phase were the XGB (R^2 = 0.572) and the RF (R^2 = 0.529) models. In contrast, the SVM model (R^2 testing = −0.039) was unsuitable for estimating the mangrove AGC at Loh Buaya (Table 1).

Table 1. Performance comparison of ML techniques on mangrove AGC estimation (bold values highlight the best-performing model)

No	Machine Learning Model	R^2 Training (80%)	R^2 Testing (20%)	RMSE (Mg C ha⁻¹)
1	Extreme Gradient Boosting (XGB)	0.892	0.572	16.45
2	Support Vector Machine (SVM)	0.747	-0.039	38.74
3	Random Forests (RF)	0.807	0.529	18.11
4	Extreme Gradient Boosting optimized by Genetic Algorithm (XGB-GA)	**0.857**	**0.758**	**15.40**

Table 2 compares the effectiveness and performances of the XGB-GA model in four scenarios (SC) for mangrove AGC estimation using difference integrations of S2B, S1A, VIs, SAR transformations, and DEM data. The XGB-GA models using the different combinations of datasets had promising results in both four SC with the R^2 greater than 0.57 in the testing phase. The XGB optimized by the GA with 12 optimal features in SC3 produced the best accuracy with the highest R^2 of 0.758 and the lowest RMSE of 15.40 Mg C ha⁻¹ as well as reduced overfitting problems in both the training and the testing phases.

Table 2. Performance of the XGB-GA model using different numbers of variables (bold values highlight the best-performing model).

Scenario (SC)	Number of Variables	R^2 Training Set	R^2 Testing Set	RMSE (Mg C ha⁻¹)
SC1	14 variables (12 MS bands of S2B data + 2 backscatter coefficients VV and VH of S1A)	0.997	0.651	21.66
SC2	27 variables (12 MS bands of S2B + 12 VIs + 2 backscatter coefficients VV & VH of S1A + DEM)	0.892	0.572	16.45
SC3	12 optimal variables (6 MS bands of S2B + 5 VIs + DEM)	**0.857**	**0.758**	**15.40**
SC4	32 variables (2 backscatter coefficients VV & VH of S1A + 30 SAR transformations)	0.991	0.573	15.82

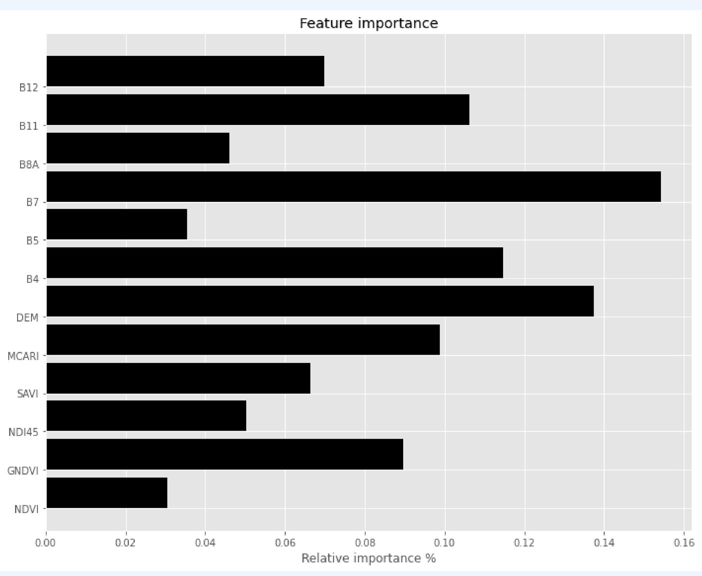

Figure 4. Importance variable

Among the 12 multispectral bands of S2B, the Red Edge-3 (Band 7 at 779.7 nm), and the Red (Band 4 at 664.9 nm) were the most sensitive to mangrove AGC in the current study, followed by the two SWIR spectra (band 11 at 1610.4 nm and band 12 at 2185.7 nm). Interestingly, among the 12 VI indices, the Modified Chlorophyll Absorption in Reflectance Index (MCARI) and the Green Normalized Difference Vegetation Index (GNDVI) were also important variables for estimating mangrove AGC in the study area, followed by the Soil-Adjusted Vegetation Index (SAVI) and the Normalized Difference Index (NDI45) (bands 4 and 5 of S2B) (see Figure 4). The DEM data showed that mangrove AGC was sensitive to elevation. It is noted that the VH and VV backscatter coefficients of the S1A C-band and their SAR transformations were likely less important and were eliminated in the final optimal 12 features selection using the GA algorithm (Figure 4).

Mangrove AGC Models

The prediction performance of the XGB-GA model for estimating mangrove AGC was improved by combining the S2B multispectral bands, VIs, and DEM datasets. Thus, the hybrid XGB-GA model was employed for generating mangrove AGC in the study area. The final results were computed to a raster in GeoTiff format for visualization. The AGC map was interpreted (Figure 5), showing the mangrove AGC ranging from 2.52 to 123.89 Mg C ha⁻¹ (average = 57.16 Mg C ha⁻¹).

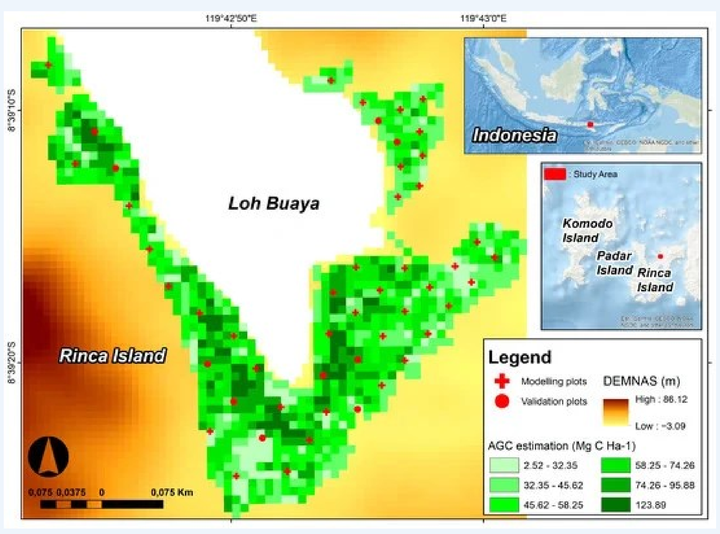

Figure 5. Spatial distribution of mangrove AGC at Loh Buaya

Conclusion

We incorporated S2B and S1A together with national DEM data into the XGB-GA model to estimate the mangrove AGC in an Indonesian mangrove area for the first time. The XGB-GA model outperformed other well-known ML models in mangrove AGC retrieval at Loh Buaya. The proposed hybrid XGB-GA with 12 optimal features estimated the mangrove AGC with the highest prediction accuracy for the first time in the Indonesian mangrove ecosystems (R2 = 0.758, RMSE = 15.40 Mg C ha 1). Interestingly, we found that new vegetation indices derived from the S2B data, such as the Normalized Difference Index (NDI45) and the Modified Chlorophyll Absorption in Reflectance Index (MCARI) were sensitively detected mangrove AGC in the Indonesian mangrove ecosystem.

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Acknowledgments

This research was funded by Badan Penelitian dan Pengabdian Masyarakat (BPPM), FPIK Universitas Brawijaya through the scheme of Lecturer Research Grant contract number 4717/UN10.F06/KS/2022 and T.D.P. is supported by a Macquarie University Research Fellowship (Grant No. MQRF0001124-2021).